# Data Product Designer: An Experimental Prototype to Support Data-Driven Decision-Making

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**Abstract**
In this paper, we examine methods to align indicator systems with strategic goals, enhancing data-driven decision-making in public administration. Additionally, we leverage Large Language Models (LLMs) and Prompt Engineering techniques to optimize data analysis and visualization workflows. We explore the integration of the Data Mesh paradigm, which treats data as a product. This approach addresses challenges in traditional data architectures, such as a lack of democratization. The research problem focuses on the strategic alignment between data-driven decision-making and governmental goals, alongside the need for effective data governance. Our proposed solution, the Data Product Designer (DPD), encompasses four core areas: Strategy, Search, Data Gap, and Analysis. AI supports these areas with non-binding suggestions, adhering to the Human-in-the-Loop principle, ensuring user control over data product development. The DPD offers a unified method that strategically aligns indicators and enhances data exchange and visualization generation. By enriching brainstorming and facilitating data needs identification and visualization, our AI-assisted approach adapts the GQM method for public sector data management. Evaluation results indicate high user acceptance, providing insights for further refinement and contributing to robust data management in public administration.

**Keywords**
Data-driven decision-making, data product, data management, AI assistance, strategic alignment

## 1. Introduction

The advent of digitalization has offered unprecedented opportunities for public administration worldwide, in particular, the potential to become data-driven [1]. Data plays a crucial role in every stage of the policy decision-making process throughout the entire policy cycle [2, 3]. Our focus is on public administration as part of policy implementation, since the administration possesses a vast wealth of data. Data-driven decision-making is increasingly shaped by emerging opportunities arising from the integration of Artificial Intelligence (AI) [4–6]. However, this transition is not without its challenges. One of the central problems is to maintain strategic alignment, resulting in ineffective use of data in the decision-making process [7–9]. Additionally, the process of data collection is often poorly digitized, further inhibiting the efficient use of data [10].

Data governance, the management and regulation of data usage, has become an essential underpinning for data-driven decision-making in public administration [11]. Research has indicated that a data-driven governance depends on several vital components, such as a nationwide data architecture, a digitally transformed public administration, and human resources equipped with the necessary skills and expertise [12]. Consequently, public administration is increasingly concentrating on two primary areas to facilitate the transition towards data-driven governance. Firstly, they leverage existing data from various sources through aggregation and analysis, and secondly, they are building (real-time) data exchange networks to enhance public service delivery (Ibid).

The research problem outlined is twofold: firstly, strategic alignment between data-driven decision-making and the government's strategic goals is challenging public administration; secondly, there is a need for effective data governance and management to be integrated with strategic and

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organizational demands. This integration is essential to establish a robust foundation for successful data-driven decision-making within complex data exchange networks. Therefore, the guiding research question is: What organizational and technical methods can enhance the development of data products in public administration?

To approach the research question, this research adopted a problem-oriented and practice-inspired approach within the framework of the Action Design Research Methodology [13]. This methodology was complemented by the use of human-centred design methods, including rapid prototyping, which allows for the creation of solutions that are both user-friendly and effective [14]. The human-centered design included different real-world use cases that we evaluated together with a pilot partner in the public sector domain. The primary limitation of our research is that the DPD was assessed exclusively within a single domain and organization, which may restrict the generalizability of the findings.

As a solution to the aforementioned research problem, the paper presents a modular data governance software toolkit, named Data Product Designer (DPD), embedded within a conceptual framework. The DPD toolkit is designed to promote an integrated, open, and analytics-driven approach to public administration. Its innovative open architecture connects business intelligence (BI) tools, different Large Language Models (LLM), data sources, and data governance applications, effectively tackling both strategic alignment and operational data management as a foundation for robust data-driven decision-making.

The prototype was developed as part of a reference implementation project for data space technology research between 2022 and 2025. It serves as an advanced smart service that can be leveraged within complex and distributed data infrastructures. This paper presents the following research contributions:

- An AI-assisted methodology to enrich the strategically aligned data product development process
- A conceptual model that bridges the gap between operational data management and strategic decision-making in the public administration
- A lightweight design approach for low threshold entry to non-technical field experts and strategists
- A flexible architecture that is designed as an interoperable framework to integrate with several data management and software stacks
- An approach to identify and overcome data gaps through AI-driven synthetic data generation

The research paper begins with an overview of related work in the section 2. Section 3 outlines the research design and overall methodology. Following this, the paper presents the DPD (section 4) as the key innovation and the evaluation results (section 5). The discussion and future research directions analyze the findings and suggest areas for future inquiry. Finally, the conclusion summarizes the key findings and their significance, restates the importance of the research problem, and highlights the contributions of the study to the field.

## 2. Related Work

In this section, we explore related work for the integration of data-driven frameworks and advanced technologies to enhance decision-making processes. This discussion illustrates how strategic data frameworks and cutting-edge AI technologies can be synergized to optimize decision-making efficiency and effectiveness.

### 2.1. Data Product Orientation

This research was particularly inspired by the new data governance paradigm of Data Mesh, especially in its emphasis on the concept of data as a product. The Data Mesh paradigm provokes treating data as a product and organizing it according to business domains [15, 16]. This approach enables teams to take distributed responsibility for data relevant to their areas, addressing challenges of traditional monolithic architectures, such as poor data quality and lack of democratization [16]. By prioritizing data as a product, Data Mesh shifts the focus from data pipelining and storage, promoting a more product-oriented data management strategy. In this paper, we recognize data products as crucial elements of indicator systems that enable effective data-driven decision-making.

### 2.2. Goal-oriented Indicator Systems

The governance model for trusted big data systems starts by adhering to important regulations, such as data protection laws, which set the framework for developing policies, principles, and procedures [17]. Policies are essentially rules that guide how users should interact with data. Principles serve as the foundation for how data is managed, reflecting societal values and expectations and emphasizing the treatment of data as a valuable asset. Procedures involve regular activities like planning cycles, the establishment of ethics committees, and conducting audits to ensure that operations are conducted smoothly and ethically. Professionals handling data are expected to follow norms specific to their fields.

It is essential for public administration to develop indicator systems and strategies that ensure that data initiatives are closely integrated with their overarching goals to fully harness the benefits of digitalization. Notable frameworks include the Balanced Scorecard [18], the Decision Maker Model [19], the Goal Question Metric [20], or the Measurement Information Model in the ISO/IEC/IEEE 15939:2017 standard [21].

The DPD utilizes the Goals-Questions-Metrics (GQM) method to establish an initial measurement framework and remains flexible to adopt other frameworks as supplementary template applications. GQM is a systematic approach to defining and interpreting a set of indicators or metrics to reach strategic alignment. This method is primarily used in the fields of software engineering [20], skills assessment [22], and cyber security [23, 24], but its principles can be applied in various contexts. The GQM method thus provides a structured way to design an indicator system that aligns with the organization's strategic and operational goals, ensuring that the collected data is relevant and valuable.

### 2.3. Large Language Model AI Application

The emergence of LLMs has significantly expanded the scope of linguistic tasks that can be automated and optimized. Such models are LLaMA 2 and GPT-4 [25, 26]. The effectiveness of these models can be further enhanced through the application of Prompt Engineering techniques, which refine input prompts to improve performance and accuracy [27]. Several key components of the DPD leverage LLMs and integrate Prompt Engineering techniques. One such technique is Chain of Thought prompting, which guides the model through a structured reasoning process by breaking down complex tasks into a series of intermediate natural language steps, ultimately leading to more accurate outputs [28]. Another commonly used technique is One-Shot and Few-Shot prompting, which involves providing high-quality, hand-crafted input-output examples to enhance model responses and improve task-specific accuracy [29]. The desk study provided a crucial basis for generating ideas on potential AI functionalities for process support and for developing a concept for lightweight, intuitive tool interaction and visual presentation. Two open-source tools that have notably influenced our project are Microsoft LIDA [30] and Chat2Vis [31]. These tools generate dataset summaries and use user-provided visualization queries to prompt an LLM, which then produces a Python-based code for chart generation. By integrating LLM-driven services with Prompt Engineering techniques, our methodology effectively improves data analysis workflows. These advancements contribute to the broader adoption of AI-driven data processing tools, optimizing efficiency and usability in data visualization and exploration. The visual representation of content and the integration of AI features were significantly inspired by Maggie Appleton [32]. In her blog post, Appleton presents several concepts illustrating how users can interact with AI beyond conventional chat interfaces.

## 3. Methodology

For developing the proposed DPD framework, we adopted the Action Design Research (ADR) methodology by Sein et al. [13]. The approach conceptualized the research process as the creation and evaluation of an IT artifact to solve organizational problems. ADR extends previous frameworks like the Design Research framework from Peffers et al. [33] by emphasizing that artifacts emerge through interactions with organizational elements and by employing an iterative process of recurring evaluation and refinement. In our case, this fitted well with our problem-oriented, practice-inspired research, conducted in constant collaboration with our pilot partners. The problem formulation phase involved a stepwise exploration of several use cases with our pilot partners from the public administration. The use cases included annually published data reports on public administration personnel management, political inquiries, and open data releases. These were utilized to analyze work processes, legal and organizational frameworks, and challenges, ultimately identifying opportunities for enhancing data product creation in public administration. According to the ADR framework, the artifact and its theoretical constructs were iteratively validated and refined.

Between May 2023 and January 2025, we developed the prototype and conceptual model iteratively and conducted six prototyping workshops with five field experts from different departments, responsible for the development of various data products within the public administration. The assessment of the protocols and transcripts from these workshops was conducted qualitatively, applying an inductive approach [34]. To facilitate the ongoing evaluation, we applied various human-centered design (HCD) methods [35]. HCD is recognized as a leading approach for systematic, user-centered system development [14]. Following HCD principles, prototyping was central to our process as basic wireframes evolved into interactive prototypes that enabled discussions on solution approaches, navigation, and design options. In order to evaluate the prototype at a mature stage, user tests were carried out with three non-technical professionals from public administration, each responsible for the development of different data products in this area. To measure the perceived usability, we supplemented the tests by using the System Usability Scale (SUS), developed by Brooke [36], a usability assessment tool based on a ten-item, five-point Likert scale questionnaire.

Complementing our practice-oriented research, we conducted a qualitative desk study to review best practices, innovative market solutions, and emerging approaches in KPI system design, data analysis, Large Language Models (LLMs), and data management. We also incorporated studies on AI user interfaces and AI-based semantic search. Desk research is recognized as a vital methodological tool in qualitative inquiry, as it provides access to a range of materials that are not originally gathered by the researcher but are instead derived from secondary sources—including academic literature, online databases, blogs, and industry reports [37, 38]. Although ADR is practice-oriented, such research provided valuable insights that informed our artifact's development and refinement.

## 4. Data Product Designer

The DPD has been developed as a research prototype to empirically explore the identified challenges and potential solutions associated with data product development in public administration. Rather than representing a finished product, the DPD serves as an experimental platform designed to investigate practical research questions in data management, analytics, and the creation of data products. The DPD is based on an AI-assisted methodology, a conceptual model, and a technical framework. The DPD is characterized by a specific design concept, developed collaboratively with our pilot partner to address the unique requirements of public administration. Creating a data product is a time-consuming process involving multiple stakeholders and requiring diverse expertise to address organizational, political, and legal parameters while ensuring data quality. Recognizing this, we formulated a vision for the artifact: subject-matter experts should be supported by an intuitive, lightweight tool that facilitates the standardized, cross-organizational development of data products without requiring complex technical expertise.

### 4.1. AI-assisted Methodology

A standardized methodology for the development of data products in the public sector offers great potential for improving harmonization and efficiency. It enables more systematic product development while fostering alignment between data-driven decisions and overarching strategic goals.

The **Data Product Designer (DPD)** was developed to support this process through a flexible **template system** that allows for the integration of various goal-oriented methods for indicator development. While the **Goal-Question-Metric (GQM)** method has been prototypically implemented due to its simplicity and structured logic from goals to questions to metrics [20], the DPD is explicitly designed to accommodate alternative approaches such as **Results-Based Management** [39], **Public Value Frameworks** [40], or **Balanced Scorecards** [18].

The current GQM-based template extends the method by linking strategic objectives to subgoals and interrelated indicators, enabling traceability and strategic alignment. Additional AI-driven support facilitates this process while reinforcing methodological consistency.

### 4.2. Conceptual Model

The DPD is built around four core areas—**Strategy, Search, Data Gap**, and **Analysis**—each supporting key phases of data product development:

- **Strategy:** Definition of goals, questions, and indicators, currently based on GQM but extendable to other methods.
- **Search:** Identification of relevant datasets via metadata catalog integration.
- **Data Gap:** Documentation of missing datasets as data demands and optional generation of synthetic data when real data is unavailable.
- **Analysis:** Creation of visualizations linked to indicators, using either real or synthetic data, supporting iterative refinement.

AI supports the entire process and is implemented in strict adherence to the Human-in-the-Loop (HITL) principle [41]. At every stage, AI provides non-binding suggestions—including draft goals, indicators, dataset recommendations, or visualization options—that users can review, edit, or discard and therefore retain full control throughout the process.

### 4.3. Technical Framework

The **technical framework** of the DPD, illustrated in **Figure 1**, is designed as an **open, modular architecture** compatible with various data management stacks. Based on a **microservices approach**, it enables scalable, maintainable integration within broader data ecosystems. The system comprises three main layers:

- **DPD Core (Figure 1: DPD Core Layer):** This foundational layer includes key modules:
  a. *StrategyMap:* A mind-map-style interface for building GQM models, enhanced by AI suggestions.
  b. *DataDiscovery* and *SemanticSearch:* Enable data exploration using traditional and AI-driven vector searches, based on StrategyMap inputs.
  c. *VizGenerator:* Transforms indicator definitions into visualizations and integrates them into external BI tools.
  d. *Data Generator* and *Data Synthesizer:* Create synthetic datasets based on identified data needs, using schema-first generation and configurable AI support.
- **AI Integration (Figure 1: AI Integration Layer):** The *PromptBroker* middleware orchestrates LLM interactions across the platform, streamlining prompt engineering and enabling flexible, model-agnostic AI integration.
- **Data Management Infrastructure (Figure 1: Data Spaces):** The DPD connects to open data catalogs (e.g., the EU Open Data Portal) and internal sources, using organizational data warehouses and analytics databases.

Overall, the DPD represents a **scalable and AI-enhanced architecture** tailored for public sector use, enabling agile, interoperable data product development.

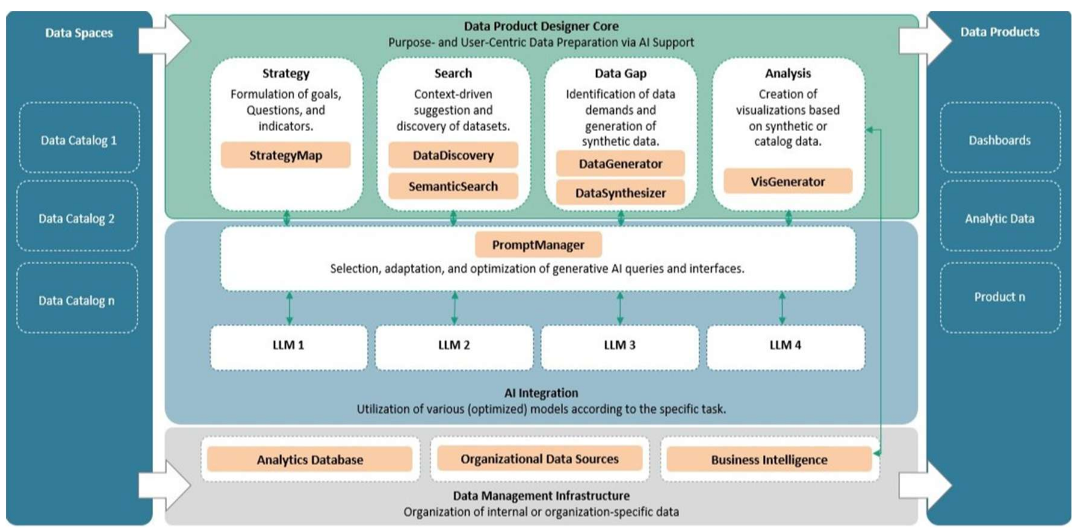


***Fig. 1.*** *Data Product Designer: Technical Framework*

### 4.4. Design Concept

The DPD interface uses familiar interaction patterns, such as a mind-map canvas, to ensure ease of use and foster methodological understanding. AI features like semantic search and data synthesis are seamlessly integrated but remain transparent and controllable via visual cues and editable suggestions. Complex functions are tucked into expandable sidebars, preserving workspace clarity.

This user-centered design, combined with modular AI support, lowers entry barriers and supports broader adoption of data-driven tools in public administration.

## 5. Evaluation results

### 5.1. Identified Problems

To gain a deeper understanding of the problems of developing data products, we evaluated our pilot partners' use cases.

The first challenging area identified was the development of strategically aligned indicators. The indicators were developed based on literature research, available data collection methods, and legal and organizational parameters. However, the resulting indicators were not aligned with strategic objectives or linked to specific measures, thereby reducing their effectiveness in guiding decision-making. Moreover, the process involved extensive interdisciplinary and cross-organizational collaboration and required approximately two years to complete the selection of indicators.

A second challenging area was the exchange of data and data management. The data collection process is characterized by a very low level of digitalization. Data is sourced from multiple origins, facing particularly high barriers due to existing media disruptions and communication via emails and third parties.

The last key challenge was the creation of visualizations. The transition from PDF-based reports to dashboard solutions was widely seen as crucial for delivering insights in a more dynamic, user-friendly, and comprehensive manner. To date, the creation of visualizations has been an elaborate process that requires technical expertise, and dashboard solutions are not available.

### 5.2. Key Findings

Through a comprehensive analysis of challenges and work processes, coupled with continuous evaluation of the methodology, the conceptual model, and the design concept, key findings emerged.

1. **Expanding and Adapting the GQM Methodology for Public Administration Needs:** The AI-supported, standardized method for indicator development was seen by the pilot partner as a valid approach to enhance quality, strategic alignment, and efficiency. While the GQM method proved helpful for ensuring strategic alignment and streamlining the process, some users preferred starting with questions rather than sub-goals. Its usefulness was closely linked to AI support, which helped overcome formulation barriers and balance user preferences. Although broadly applicable, it remains unclear whether GQM is the best methodological fit. Flexibility to adapt the method to specific contexts was considered essential. Still, the adapted GQM method in its traditional form does not fully address the needs of public administration and data product creation. To address this gap, the GQM framework was extended to include data discovery, data demand, data gap analysis, and synthesis. This resulted in an integrated model tailored to the complexities of public governance.
2. **The Need for a More Intuitive and Visual Approach:** Previously used data and knowledge management tools were insufficient for the complex demands of data product development and required collaboration, often posing technical barriers for non-experts. To address this, our design principles aimed to integrate key steps of data product creation into a single tool, use a visual interface, and embed context-aware AI support. Evaluation showed that the canvas-based, mind-map-like interface of the DPD, combined with AI suggestions and a data sidebar, provided a low-threshold entry point to data product development. The DPD achieved an average SUS score of 70, indicating good usability. The integration of AI into the

strategy map was seen as intuitive and helpful. Participants also expressed interest in more flexible interaction, such as searchable data catalogs entering questions like political queries.

3. **AI-Powered Support for Data-Driven Workflows:** AI support helped address the identified problems of indicator development, data management, and visualization:
    a. *Supporting Brainstorming and Methodological Adaptation:* In sample runs of the GQM-method, many AI suggestions were adopted or aligned with user ideas; even unused suggestions supported brainstorming and eased method entry.
    b. *Improving Data Discovery and Data Demand Management:* Locating relevant datasets in the vast open data landscape remains challenging. The DPD improved data discovery through AI-based semantic search across multiple catalogs, such as the European Open Data Portal. However, the success of data discovery efforts depends critically on the quality of the metadata associated with these datasets. Replacing the initial method with a vector-based approach improved results and reduced reliance on high-quality metadata. Still, human involvement remains essential to assess the relevance and suitability of suggested data. Evaluation revealed the need for a clear understanding of organizational data needs. The DPD contributes to this by facilitating the documentation and communication of data demand across different departments.
    c. *Reducing Technical Barriers and Addressing Data Gaps Through Synthesis:* AI-generated visualizations made complex data more accessible, which enables a broader range of stakeholders to contribute to data product elaboration. However, a major obstacle was the need for pre-processed data compatible with BI tools. Additionally, data gaps and restrictions on sharing sensitive data often limit analysis. To avoid interrupting the creative process, the DPD was extended with an option to generate synthetic data.

    Overall, user attitudes toward AI use in the DPD were shaped by subjective norms. While AI integration was seen as central to perceived usefulness, skepticism remained and should be further addressed. One proven measure to increase acceptance of AI in the public administration was the integration of open source models such as LLaMA and Mixtral.

Collectively, the evaluation of the DPD as a research prototype provides valuable insights into both methodological and technological challenges associated with transitioning to data-driven governance. Although the DPD remains a research prototype, its experimental deployment has contributed significantly to the development of flexible and user-friendly data management infrastructures to support the data product creation process in public administration.

## 6. Discussion and future research directions

The research aimed to tackle the core issue of maintaining strategic alignment, which leads to the ineffective utilization of data in decision-making processes within public administration. In the course of our evaluation of the DPD, we identified several challenges that shape future research directions.

One significant issue was the lack of widely accepted methods for deriving indicators within public administration. This challenge might be mitigated by concentrating on specific areas that utilize more specialized monitoring systems, such as security or risk management. New monitoring systems would also provide the basis for creating new templates that can be adapted to the strategy map.

The flexible architecture of the DPD allows for seamless integration of existing IT components, enhancing interoperability. A challenge lay in the integration and utilization of metadata catalogs. The quality of metadata often varies, which can lead to inconsistencies and challenges in data integration and usability. Therefore, a potential future extension of the DPD is the integration of AI-based functionality to enhance and harmonize the quality of metadata. Further, connecting internal data sources such as data warehouse applications and various relational databases presents a future research challenge. Establishing robust connectors and ensuring seamless integration will be crucial for leveraging existing data assets effectively within the public sector's heterogeneous IT landscapes.

AI plays a crucial role by facilitating the creation of data products. Further research should examine how to improve user comprehension, validation, and interaction with AI-generated content in public administration. At present, the DPD lacks a feedback mechanism that involves human input. Domain-specific prompt customization is supported by the Prompt Broker and is currently carried out by supervising experts in collaboration with relevant user groups. Nonetheless, the potential of human feedback to improve the quality of AI suggestions remains an important area for investigation. A key challenge identified is the need for users to verify the accuracy of visualizations. Future enhancements could include explanatory text or additional supportive elements to facilitate interpretation and ensure correctness. Moreover, future research should examine whether governance and compliance standards may conflict with AI-generated suggestions and how such risks can be proactively mitigated. We propose the integration of an AI-powered synthesizer as a Data Generator component. One of the current research challenges is to generate synthetic data that closely mirrors real-world data. In the future, the step of metadata generation and its requirements in the public sector must be examined. For instance, specific types of administrative metadata could be made available for selection to meet the unique needs of public administration.

These challenges highlight the need for ongoing enhancements of the DPD framework to ensure it remains adaptive and responsive to the evolving needs of data-driven governance in the public sector.

## 7. Conclusions

This paper addresses the question of what organizational and technical methods can enhance the development of data products in public administration with a problem-oriented and practice-inspired approach. Our problem formulation identified three challenging areas: developing strategically aligned indicators, data exchange and management, and generating visualizations. This paper presents a conceptual model, design concept, and technical framework that illustrate the research prototype DPD, which offers a solution to these challenges. The evaluation confirmed that these challenges can be effectively tackled through a unified method that guides users through the process and ensures the strategic alignment of indicators. Furthermore, utilizing AI enriches brainstorming, assists in identifying relevant datasets and data needs, and facilitates the generation of visualizations and synthetic data. Our work also contributed to investigate which methodological approach foster data product development and integration to achieve high user acceptance in public administration. This is achieved by further developing the GQM method into an AI-assisted approach specifically adapted to the requirements of public sector data management.

Evaluation results offered insights into the perceived usefulness and usability from the pilot partner's perspective, forming the basis for further refinement of the DPD through the integration of data demand capture and synthetic data generation to close data gaps. Overall, the DPD contributes to establishing a robust and user-friendly data management infrastructure in the public administration, bridging the gap between strategic data analytics and operational data management and governance. However, the evaluation also highlighted the need for further in-depth investigation, particularly in ensuring the trustworthiness and traceability of AI-generated results, enhancing interoperability with internal data sources, and designing AI-driven generation of high-quality, domain-specific synthetic data in a targeted and demand-oriented manner while maintaining privacy and security. While previous experiences in developing data products contributed to the evolution of the DPD, the fact that the DPD was evaluated solely within one domain and organization represents the greatest limitation of our project. Consequently, future studies should explore its adaptation in other contexts and approaches for refining the indicator derivation method. Moreover, future research should focus on the integration and standardization of metadata catalogs, enhancing the semantic description of datasets to improve data quality and usability, and developing robust connectors to seamlessly integrate diverse internal data sources within the public administration's IT landscape.

Overall, the DPD demonstrates its ability to enable collaborative data product creation, enhance the strategic alignment of indicators and data exchange, and generate initial visualizations without requiring technical expertise. This concept holds significant potential to strengthen the role of subject-matter experts, expedite the collective decision-making process regarding focus indicators and their visualization, and ensure that these indicators are aligned with the strategic needs of the organization.

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## 9. Declaration on Generative AI

During the preparation of this work, the authors used GPT-4 in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication’s content.

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